Mitigating Effect of Regional Textile Industry Chain Resilience on Economic Fluctuations

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ABSTRACT Despite increasingly frequent disruptions in global supply chains, systematic quantitative research and regional comparisons on how textile industry chain resilience mitigates external economic shocks remain limited. This study constructs a three-dimensional resilience evaluation framework incorporating supply stability, synergy strength, and recovery speed based on input–output tables and enterprise linkage data, and quantifies the overall resilience level using the entropy method. Complex network analysis is employed to identify key nodes and shock transmission paths within the industrial chain, revealing structural vulnerabilities and propagation characteristics. Furthermore, a spatial Durbin model is developed to establish a regional spatial response framework that captures both direct and indirect marginal effects of resilience enhancement on economic fluctuations from local and neighboring perspectives, forming an integrated "measurement–identification–response" methodology. Such network-oriented modeling also provides useful references for distributed information transmission and resilient infrastructure optimization in intelligent electromagnetic and communication systems. Experimental results show that industry chain resilience is negatively correlated with GDP volatility (correlation coefficient of -0.112), while resilience enhancement reduces economic volatility across eight provinces. The total effects in Jiangsu and Guangdong reach 5.0%, with more than 50% of the mitigation benefit attributed to industrial restructuring, demonstrating that strengthened regional resilience effectively suppresses economic shocks and generates significant spatial spillover effects.

INDEX TERMS economic fluctuation, industrial chain resilience, complex network analysis, spatial durbin model, resilient information network

I. INTRODUCTION

REGIONAL economic development continues to be affected by the volatility of the global supply chain and external economic shocks. The global industrial chain has regularly experienced disruptions in recent years with the introduction of trade frictions, pandemics, and geopolitical risks in an orientation that left the regional textile industry facing multiple pressures such as disruption to production and lower demand, and increased prices of raw materials [1,2]. The textile industry is a labor-intensive and export-oriented industry that contributes significantly to regional employment and value-added manufacturing output, and the stability of the industrial chain is critical to economic resilience and social stability [3,4]. Traditional frameworks for analyzing fluctuations of the economy focus on cyclical fluctuations and structural adjustments of macroeconomic indicators at a more general level than the immediate industrial chain structure [5,6]. Insufficient resilience in the industrial chain often allows local shocks to diffuse rapidly in the supply chain and leads to amplified or extended transmission effects of economic fluctuations. Existing academic research on textile industry resilience across the industrial chain remains more qualitative with minimal systematic quantitative analysis or identification of regional variations in its ability to mitigate local or regional economic fluctuations [7,8]. A deficiency of this type limits the degree to which policy can be formed about optimizing the industrial structure (and consequently, regional economies) and increasing resilience to local or regional real or nominal shocks.

Scholars from both at home and abroad have conducted multi-faceted studies on the relationship between industrial chain and economic stability. Some of them study the effect of the adjustment of industrial structure on economic stability from the perspective of macroeconomic fluctuation model, and some scholars study the impact of industrial chain disruption on production systems from the perspective of supply chain management and organization. Research on supply chain resilience has been combined into a multidimensional analytical framework. Patel et al. [9] developed a co-operative association model in the Indian textile industry to manage supply chain disruptions. Nagariya et al. [10] looked at the mechanism of blockchain technology to explore how it could enhance supply chain resilience from the resource-based view perspective, while Irfan et al. [11] focused on the core role of knowledge management and dynamic capabilities in the resilience model. Singh [12] further demonstrated the mechanism of enhancing supply chain resilience through multi-layered flexible strategies. Butollo et al. [13] analyzed global supply chains' continued reliance in the post pandemic era from the perspective of technological sovereignty. At the evaluation method level, Sharma et al. [14] developed a resilience implementation evaluation framework, and Bui et al. [15] verified the causal relationship of resource management in circular supply chains through the case of the Indonesian textile industry. The latest research trends indicate that the textile industry is undergoing a paradigm shift from Industry 4.0 to Industry 5.0 [16], which provides a new perspective for understanding the relationship between digital transformation and industrial chain resilience. In addition, some studies use a single statistical regression model to analyze the relationship between resilience and economic fluctuations, but fail to consider spatial correlation and inter-regional spillover effects, resulting in the difficulty of explaining the actual role of regional coordination in economic stability in the research conclusions.

In terms of research methods, existing literature has proposed a variety of quantitative methods to measure industrial resilience and economic stability. Some scholars use input-output analysis to track the transmission path of shocks in the industrial system and infer the degree of impact of fluctuations through the input relationship between industries [17,18]. Another group of scholars uses complex network models to describe the structural characteristics of the industrial chain and reveal the buffering or amplification functions of key nodes in the supply system [19,20]. Some studies have also applied spatial econometric models to analyze the impact of regional industrial agglomeration on economic fluctuations and try to capture the economic linkage effect between neighboring regions [21]. These methods are valuable in depicting the relationship between industrial structure and economic fluctuations, but most studies have not combined the industrial chain resilience index system with the spatial effect model, making it difficult to systematically reveal the dynamic response mechanism of regional textile industry chain resilience to economic fluctuations [22,23]. The construction of the index system mostly remains at the static description level, lacks a comprehensive analysis of the relationship between the endogenous factors of resilience, and does not systematically compare regional differences [24]. In response to the above shortcomings, this paper applies network resilience analysis and the spatial Durbin model to construct a comprehensive analysis framework to break through the limitations of traditional research in spatial structure identification and dynamic transmission mechanism characterization. This study aims to reveal the mitigating mechanism of regional textile industry chain resilience during economic fluctuations and quantify its spatial spillover effects. Methodologically, this study systematically bridges the gap between resilience measurement and spatial response. It theoretically reveals the transmission logic of industry chain structural characteristics on regional economic stability and, in practice, provides quantitative support for the development of highly resilient regional textile industries and the construction of risk-resistant systems.

II. REGIONAL TEXTILE INDUSTRY CHAIN RESILIENCE ANALYSIS FRAMEWORK

CONSTRUCTING A REGIONAL TEXTILE INDUSTRY CHAIN RESILIENCE INDEX SYSTEM

INDEX SYSTEM CONSTRUCTION AND DATA PROCESSING

Based on regional input-output tables and enterprise-linked data, this study constructs a three-dimensional resilience indicator system: "supply stability, synergy intensity, and recovery speed." Data sources include national and provincial input-output tables, enterprise registries, lists of supporting enterprises in the industrial chain, and local statistical yearbooks. The intermediate input structure of the textile industry is used to extract a supply chain upstream and downstream correlation matrix, identifying regional industry supply and demand dependencies. Input-output data are then deflator-adjusted to generate comparable physical quantitative data [25,26]. Enterprise-linked data are used to construct a matrix of transaction frequency and cooperation intensity, which is then converted to dimensionless data in the [0, 1] range through range normalization to ensure the stability of the entropy method.

The supply stability dimension is measured by a weighted combination of regional raw material self-sufficiency rate, supplier concentration, and import dependence; the synergy strength dimension is calculated based on the average degree of the enterprise network, the clustering coefficient, and the rate of change of the proportion of industrial input; the recovery speed dimension is measured by the output value recovery cycle and production capacity repair speed during the historical shock period, and the recovery path slope is extracted by time series smoothing to reflect the adjustment ability of the system after the disturbance [27].

INDICATOR WEIGHTING AND COMPREHENSIVE MEASUREMENT

To determine the relative importance of each indicator and avoid subjective weighting bias, the entropy method is used to objectively weight the resilience indicators. Let the standardized value of the i-th region on the j-th indicator be x_{ij}, then its weight under this indicator is given by formula (1):

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \tag{1}$$

The information entropy value of the j-th indicator is calculated as formula (2):

$$e_j = -k \sum_{i=1}^{n} p_{ij} \ln p_{ij}, \quad k = \frac{1}{\ln n} \tag{2}$$

Based on this, the indicator weights are obtained $w_j = \frac{1-e_j}{\sum_{j=1}^{m}(1-e_j)}$, and the comprehensive score $R_i = \sum_{j=1}^{m} w_j x_{ij}$ of the regional textile industry chain resilience is obtained. This calculation process reflects the contribution of each dimension to comprehensive resilience through the degree of dispersion of the indicators, making the final results objectively comparable.

This study employs a two-stage weighting strategy: first, all original sub-indicators (a total of nine) across the three dimensions of supply stability, coordination strength, and recovery speed are standardized. Second, all nine sub-indicators are uniformly incorporated into the entropy method calculation to directly generate objective weights for each sub-indicator, which are then summed to obtain the regional comprehensive resilience index. Therefore, the final resilience index is entirely data-driven, without secondary weighting of the three dimensions, thus minimizing subjective weighting bias. Although the selection of sub-indicators is still based on the theoretical framework, the internal consistency of the indicator system is verified through principal component analysis, ensuring the robustness of the construction logic.

After weights are determined, the three-dimensional resilience scores for each region are normalized to form a unified regional resilience index. Principal component analysis is used to verify the rationality of the weight distribution. Consistency between the load and entropy weights indicates a robust system architecture. The annual rate of change in the resilience index is then calculated to reflect the dynamic evolution of the regional textile industry chain.

Figure 1 shows the resilience characteristics of the regional textile industry chain and its dynamic changes in different regions. The horizontal axis of Figure 1(a) shows the comprehensive resilience index of each region, and the vertical axis shows the region name. The comprehensive resilience index of key mid- and upstream textile regions such as Jiangsu, Zhejiang, and Guangdong is relatively high, reflecting that these regions have strong buffering capabilities in terms of supply stability, synergy intensity, and recovery speed. Figure 1(b) shows the evolution trend of the resilience index of the top five key regions from 2015 to 2023, with the horizontal axis showing the year and the vertical axis showing the resilience index. The resilience index of Jiangsu and Zhejiang shows a steady upward trend, indicating that these regions have strong recovery speed and synergy efficiency in responding to external economic fluctuations. This shows that there are significant differences in resilience among regions, highlighting the key role of industry chain resilience in mitigating economic fluctuations.

IDENTIFYING KEY NODES AND TRANSMISSION PATHS IN THE INDUSTRIAL CHAIN

NETWORK CONSTRUCTION AND NODE FEATURE CALCULATION

Based on the enterprise association database and input-output department pairing information, this study constructs a complex network structure of the regional textile industry chain. With enterprises or industrial sectors as nodes and transaction relationships or input dependencies as edges, a weighted directed network is formed. The weight is determined by the proportion of transaction volume, and the direction is from upstream supply to downstream demand. During the data processing stage, weak connections with annual transaction volumes below a set threshold are removed to increase network sparsity and reduce the impact of noise. Subsequently, the connections between enterprises in multiple regions are mapped to the provincial level to form a cross-regional supply chain network matrix. The node degree value is used to reflect the number of connections of an enterprise in the industry chain. The out-degree represents the supply relationship to the downstream, and the in-degree represents the degree of dependence on the upstream [28,29]. All indicators are calculated based on the adjacency matrix $A = [a_{ij}]$, where a_{ij} represents the input association strength of nodes i to nodes j. During the network topology feature extraction stage, the betweenness centrality, closeness centrality, and weighted degree value of each node are calculated. Betweenness centrality reflects the control ability of a node on the shortest path and is calculated as Formula (3):

$$BC_i = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{3}$$

σ_{st} represents the number of shortest paths between nodes s and t, and $\sigma_{st}(i)$ represents the number of shortest paths passing through node i. By calculating BC_i, it can be identified nodes that play a key intermediary role in the transmission process of the industrial chain. A node's closeness centrality, calculated as the inverse of the shortest path length, characterizes its information proximity within the overall network. By combining degree distribution with betweenness distribution analysis, nodes with both high connectivity and high control power within the industrial network are identified as potential key nodes. To eliminate the influence of accidental extreme values, the centrality index is standardized, and the quantile threshold method is used to determine the set of key nodes. This process ensures the stability and repeatability of the network structure identification results.

CONDUCTION PATH IDENTIFICATION AND SHOCK DIFFUSION SIMULATION

After the key nodes are identified, the shortest path search and network connectivity analysis are used to simulate the transmission path of external shocks in the industrial

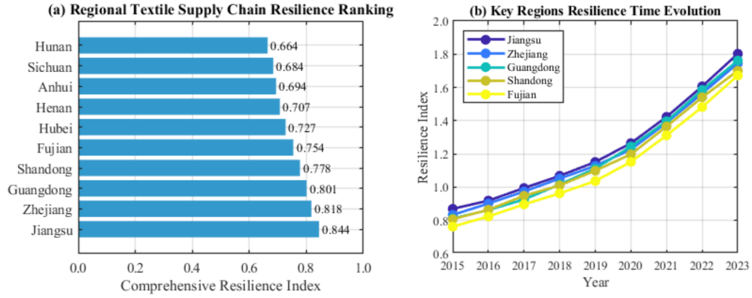

FIGURE 1. Analysis of the resilience of the regional textile industry chain. (a) Ranking of comprehensive resilience index of regional textile industry chains; (b) Temporal evolution trend of resilience index in key regions

chain. The study takes the input-end shock (upstream raw material supply disturbance) and the demand-end shock (downstream market contraction) as the starting point, and calculates the propagation direction and distance of the shock in the network through the weighted path algorithm. The transmission intensity is represented by the product of the edge weights on the path, and the transmission speed is determined by the number of path levels. To analyze the transmission effect among multiple regions, a partition weight matrix $W = [w_{ij}]$ is constructed, where w_{ij} represents the impact intensity of the industrial shock of region i on region j, which is weighted and calculated according to the actual trade dependence [30]. Through matrix iteration, the cumulative value of the shock received by each node in the multi-step transmission is obtained, and the quantitative identification of the shock diffusion trajectory within the industrial chain is achieved.

To characterize the buffering effect of network resilience, it applies node removal and edge break simulations. Nodes with the highest betweenness centrality are removed sequentially, and network connectivity and the average shortest path change rate are calculated to assess the ability to maintain connectivity after key node failures. A low overall efficiency decline indicates that the industrial chain structure has redundancy and substitutability, indicating high resilience.

Figure 2 illustrates the structural characteristics of the regional textile industry chain and its transmission patterns when subjected to external shocks. In Figure 2 (a), nodes represent industry links; arrows represent input-output relationships; node size and color reflect the level of betweenness centrality, indicating its criticality in the flow of information and resources in the industry chain. Midstream links such as spinning, weaving, and machinery are at the center of the network, demonstrating strong connectivity and control capabilities. Figure 2 (b) shows the shock transmission intensity matrix, with the horizontal axis representing the receiving node and the vertical axis representing the source node. The color depth indicates the intensity of the shock transmitted from the source node to the receiving node. The spinning and weaving nodes have the most significant impact on multiple downstream links, with high-intensity transmission to the wholesale node, indicating that changes in the resilience of key links have the greatest impact on the entire industry chain.

During the simulation process, the propagation results of each path are standardized, and the propagation intensity matrix is matched with the resilience index obtained by the previous entropy method to verify the correspondence between the network structure characteristics and the resilience level.

In Figure 2(a), the area of a node is proportional to the original value of its betweenness centrality, visually representing the relative importance of the node in the network's mediation role; the color saturation of the node (from light blue to dark red) corresponds to the normalized value of its betweenness centrality after min-max normalization, ranging from [0, 1]. Although both originate from the same indicator, they serve the purposes of structural prominence and visual recognition, respectively, ensuring that the reader can simultaneously perceive the absolute influence and relative ranking of the nodes.

CONSTRUCTING A SPATIAL RESPONSE MODEL OF RESILIENCE TO ECONOMIC FLUCTUATIONS

SPATIAL DATA SETTING AND WEIGHT MATRIX CONSTRUCTION

This study constructs a panel data framework using the annual GDP volatility of each region as the explained variable and the regional textile industry chain resilience index as the core explanatory variable. The data covers multiple consecutive years and all sample regions, with the temporal and spatial dimensions arranged side by side to form a bidirectional spatiotemporal observation matrix. To ensure data stationarity, the natural logarithm of the GDP series is taken, and the annual growth rate is calculated. The volatility series is then extracted using standard deviation smoothing to obtain a measure of regional economic fluctuations [31,32]. The resilience index, derived from the entropy method measurement results previously described, is applied to the model as a structural variable of the regional economic system.

The spatial weight matrix $W = [w_{ij}]$ is constructed based on the dual criteria of geographic contiguity and economic linkage. Geographic contiguity weights are weighted using the queen's contiguity criterion, assigning a value of 1 to adjacent regions and 0 to all others, with row normalization applied. Economic linkage weights are calculated based on

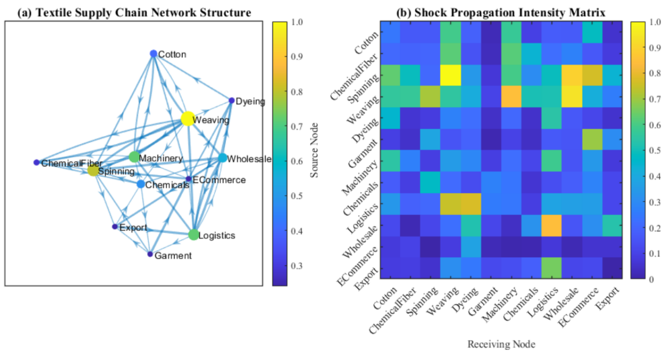

FIGURE 2. Schematic diagram of the complex network structure and shock transmission path of the textile industry chain. (a) Complex network structure of the textile industry chain; (b) Industry chain shock transmission intensity matrix

the proportion of textile industry trade between regions, with regions with larger trade volumes given higher weights to reflect the strength of economic ties. A comprehensive matrix is generated by linearly weighting the geographic and economic weights, with weight parameters determined based on correlation test results. By setting the matrix's diagonal elements to zero, the influence of individual regions is eliminated, ultimately forming a weight matrix that can manipulate spatial lag effects.

To determine the linear combination coefficients of the geographical adjacency weight matrix W_g and the economic linkage weight matrix W_e, the partial correlation coefficients between each matrix and the spatial lag term of the explained variable (GDP volatility) are calculated, and the combination proportion that yields the highest log-likelihood of the spatial model is selected through cross-validation. Ultimately, $W = 0.6W_g + 0.4W_e$ is adopted, which demonstrates the best spatial explanatory power in both the LM and Hausman tests and passes the robustness test. The steps for measuring regional GDP volatility are as follows: first, the annual real GDP growth rate is calculated; second, using a five-year window, the growth rate series are smoothed using the central moving average method to remove short-term noise; finally, the standard deviation of the smoothed growth rate series is calculated as the economic volatility of the region within that window. This method, compared to directly using the standard deviation of the original annual growth rate, more stably reflects medium- and long-term volatility trends and is suitable for panel regression analysis.

SPATIAL MODEL SETTING AND PARAMETER ESTIMATION STEPS

In the spatial correlation test stage, Moran's I index is used to test the spatial dependence of economic fluctuations. If the result is significantly positive, it indicates that there is spatial aggregation between regions, which is the premise for building a spatial model. Subsequently, LM (Lagrange Multiplier) test and Robust LM test are carried out to determine the significance of spatial lag effect and spatial error effect. According to the test results, the spatial Durbin model (SDM) is used as an analysis tool to capture both the regional self-effect and the neighboring spillover effect [33]. The model form is set as Formula (4):

$$y = \rho W y + X\beta + WX\theta + \mu + \epsilon \tag{4}$$

y represents the regional GDP volatility vector; X is the explanatory variable matrix containing the textile industry chain resilience index and control variables (industrial structure, fixed asset investment ratio, employment density, etc.); W is the spatial weight matrix; ρ is the spatial autoregressive coefficient; β and θ denote the direct effect and spillover effect parameters; μ is the individual fixed effect; ϵ is the random error term. The parameters are solved using the maximum likelihood estimation method to ensure the unbiased and consistent estimation results.

After parameter estimation, the model residuals are tested for spatial independence. If Moran's I is insignificant, the model has effectively incorporated the spatial correlation structure. To test the model's robustness, a spatial autoregressive model (SAR) and a spatial error model (SEM) are constructed for comparative estimation. If the SDM model has the highest log-likelihood value, and its parameters are more significant than those of the other models, its suitability is confirmed. By decomposing the spatial effect, the total effect is divided into direct and indirect effects to measure the magnitude of the impact of increased industrial chain resilience on economic fluctuations in the local and neighboring regions [34,35]. To prevent multicollinearity from impacting the stability of the results, variance inflation factor (VIF) tests are performed on the explanatory variables, and unit root and cointegration tests are performed on the variable series to ensure that the model settings meet stationary conditions. For panel samples with a long time dimension, fixed-effect estimation is used to control for time trends. Through a systematic modeling process, a spatial response framework for the relationship between resilience and economic fluctuations is established.

Figure 3 illustrates the spatial impact of regional textile industry chain resilience on economic fluctuations. Figure 3(a) shows the standardized GDP volatility of each province on the horizontal axis and the standardized spatial lag term on the vertical axis. The scatter plot and fitted line indicate a positive correlation between economic fluctuations and geographical factors. The Moran index I value is 0.412, indicating that regions with strong resilience experience less economic volatility and are less affected by surrounding areas. Figure 3(b) shows four explanatory variables on the horizontal axis: resilience index, fixed asset investment, industrial structure, and employment density. The vertical axis represents the effect coefficients. The effect decomposition results of the spatial Durbin model show that the resilience index has a significant negative direct effect (coefficient approximately -0.29) and a negative indirect spillover effect (coefficient approximately -0.19) on GDP volatility, with a total effect of -0.48. This indicates that enhancing the resilience of the regional textile industry chain can not only effectively suppress local economic fluctuations but also reduce the volatility level of neighboring regions through spatial spillover mechanisms.

The Moran index I value is 0.412 ($p < 0.01$), indicating a significant positive spatial autocorrelation in the GDP volatility of different provinces. This means that high-volatility regions tend to cluster together, and low-volatility regions also tend to cluster. This result verifies that economic volatility exhibits a clear regional clustering characteristic, providing a basis for the specification of spatial econometric models.

III. REGIONAL RESILIENCE MITIGATION EFFECT ASSESSMENT

The data used in this study primarily comes from the "China Input-Output Table" published by the National Bureau of Statistics, provincial statistical yearbooks, and local economic operation bulletins. Industrial chain structure data includes intermediate input and output information from the textile industry and its upstream and downstream related industries, and a matrix of inter-regional industrial linkages is extracted. Enterprise-level data, including textile enterprise directories and financial data from the National Enterprise Credit Information Publicity System and the Wind database, is used to construct a network of enterprise linkages. Macroeconomic data includes provincial GDP, employment, fixed asset investment, and textile industry value added from 2015 to 2023, converted to comparable prices at current prices, and volatility is calculated. Trade and logistics data is sourced from the China Customs Statistics and Transportation Yearbook to supplement the strength of inter-regional economic linkages.

ASSESSMENT OF ECONOMIC FLUCTUATION STABILITY

The stabilizing effect of resilience on economic fluctuations is assessed using regional GDP volatility. The standard deviation of each region's annual GDP growth rate is calculated to generate time series volatility data. The textile industry chain resilience index is paired with the volatility series to calculate the dynamic difference. The panel regression residual variance ratio method is used to compare the convergence of economic volatility variance before and after resilience improvement. A significant decrease in the residual variance indicates that increased resilience has suppressed volatility. Finally, a sliding window smoothing approach is used to examine fluctuation trends across different years and assess the sustainability and stability of the mitigation effect.

Figure 4 (a) shows the relationship between the industry chain resilience index and GDP volatility for 12 major textile provinces from 2015 to 2023. The horizontal axis represents GDP volatility (%); the vertical axis represents the resilience index; the color of the scattered points indicates the chronological order. The overall trend shows that data points with higher resilience indices correspond to lower GDP volatility, indicating that regions with more resilient industry chains are able to effectively mitigate economic fluctuations. The fitted line has a negative slope and a correlation coefficient of approximately -0.112, indicating a significant negative correlation between resilience and economic fluctuations.

Figure 4 (b) compares the average GDP volatility of each province before (2015-2019) and after (2019-2023) increased resilience. The horizontal axis shows the province, and the vertical axis shows the average volatility (%). Overall, volatility decreases in all eight provinces, with Anhui and Jiangsu experiencing the largest decreases. This decline demonstrates the mitigating effect of increased resilience on economic fluctuations.

REGIONAL SPILLOVER EFFECT ASSESSMENT

To identify the transmission effects of changes in regional resilience on neighboring economies, a spatial effect decomposition method is used to assess spillover strength. First, the indirect effect parameters between neighboring regions are extracted based on a constructed spatial Durbin model. The average magnitude of the inter-regional impact is calculated using a spatial weight matrix. Second, a counterfactual simulation method is used to simulate a hypothetical scenario in which the resilience index of the target region increased by 10%. The predicted volatility changes in neighboring regions are recalculated to measure the diffusion of the improved economic stability. Finally, the spillover paths are grouped by geographic proximity and industrial linkages, and interval comparisons are conducted to identify the spatial gradient of the spillover effect.

Table 1 shows the transmission effects of increased regional resilience on economic volatility within and across neighboring regions, assessing the spatial spillover effects of increased resilience in the textile industry chain. The "Own Effect" in the table represents the reduction in GDP volatility resulting from a 10% increase in resilience within the target region. The "Indirect Effect" denotes the value which the impact of the resilience of the particular region had on the average volatility of nearby regions. There is the "Total Effect", indicating to the sum of both direct effects and indirect effects as well. The "Predicted Volatility Reduction" accounts for the predicted decrease in economic volatility in neighboring regions based on counterfactual simulations.

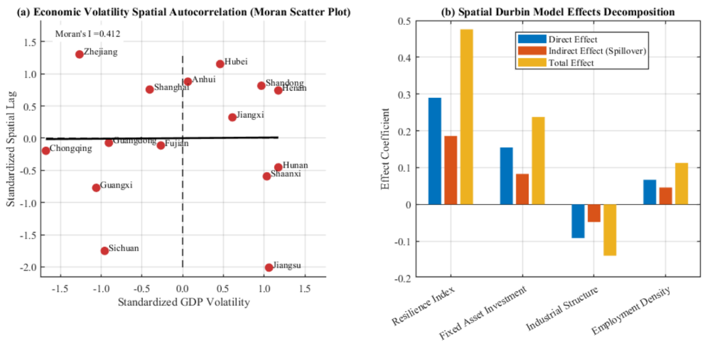

FIGURE 3. Analysis of spatial effect of regional textile industry chain resilience. (a) Spatial Autocorrelation of Economic Fluctuations (Moran Scatter Plot); (b) Histogram of the decomposition of the spatial Durbin model effect

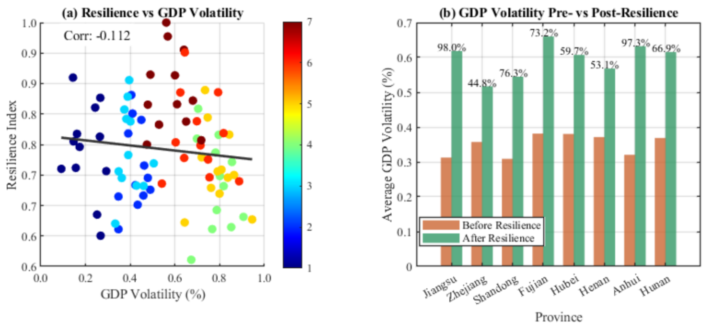

FIGURE 4. Assessment of economic fluctuation stability. (a) Scatter plot of industrial chain resilience and GDP volatility; (b) Comparative histogram of GDP volatility before and after resilience improvement

Jiangsu Province yielded the largest direct effect of 3.2%, with an indirect effect of 1.8%, with a total effect of 5.0%. The neighboring regions predicted volatility decreases by about 2.4%, indicating that the increased resilience of Jiangsu Province demonstrates not only a stabilizing effect on its own economy, but has a marked mitigating effect on the neighboring region as well. The results show that while Guangdong Province exhibits a direct effect of only 2.5%, that indirect effect is 2.5%, for a total indirect effect is 5.0%, suggesting if its increased resilience this province is effective at transmitting that increased resilience to neighboring economies. Sichuan Province has direct and indirect effects of only 1.7% and 1.2%, respectively, for a total indirect effect of only 2.9%. Notably, the predicted volatility for neighboring regions coefficient decreases by only 1.3%. These results indicate that inland geographies exhibit relatively weaker spatial spillover effects. Overall, enhanced resilience of the economically developed coastal provinces especially, Jiangsu, Guangdong and Zhejiang improve their own economic stability, as well as mitigate regional economic fluctuations through their industrial chains and geographic proximity.

TABLE 1. Assessment of regional resilience spillover effects

Region	Own Effect (%)	Indirect Effect (%)	Total Effect (%)	Predicted Volatility Reduction (%)
Jiangsu	3.2	1.8	5	2.4
Zhejiang	2.8	2.1	4.9	2.2
Guangdong	2.5	2.5	5	2.5
Shandong	2.9	1.6	4.5	2
Fujian	2.4	1.9	4.3	1.8
Hubei	2	1.5	3.5	1.6
Henan	1.8	1.3	3.1	1.4
Sichuan	1.7	1.2	2.9	1.3

INDUSTRIAL STRUCTURE ADAPTABILITY ASSESSMENT

To examine the role of industrial restructuring in the resilience mitigation mechanism, an industrial structure adaptability index is constructed to assess the degree of regional industrial structure alignment. First, the industrial structure change series is calculated based on the output value share of the textile industry and related supporting industries in each region. Second, by comparing changes in the resilience index with the rate of industrial structure change, the synchronous relationship between structural adjustment and the stability of economic fluctuations is determined. The time-series difference method is used to measure the change in industrial structure concentration before and after the resilience change to identify the proportion of structural adjustment's contribution to volatility mitigation. Finally, combined with a multiple regression residual analysis, after eliminating the influence of the external economic environment, the net effect of structural adjustment is extracted to measure the actual contribution of regional industrial adaptability in mitigating economic fluctuations.

Table 2 illustrates the effect of regional industrial restructuring on enhancing the resilience of the textile industry chain. "Industrial Concentration Before and After Adjustment" reflects the degree of optimization in industrial layout; "Change in Resilience Index" indicates the magnitude of capacity improvement; "Structural Adaptability Contribution" quantifies the contribution of structural adjustment to resilience enhancement. The results show that in Jiangsu, industrial concentration increases from 68% to 72%; the resilience index increases by 0.06; the structural adaptation contribution reaches 50%, indicating that structural optimization significantly enhances its economic stability. In Guangdong, concentration increases from 60% to 66%, and the resilience index also increases by 0.06, but the contribution rate is even higher at 55%, indicating a more prominent effect of structural adjustment. In Henan, concentration only increases from 50% to 53%; the resilience index increases by 0.02; the contribution rate is 30%, a relatively small increase. Overall, coastal areas significantly enhance the resilience of the textile industry chain through structural optimization, while the improvement in central regions is relatively limited.

TABLE 2. Industrial structure adaptability assessment

Region	Industry Concentration		Resilience Index	Structure Adaptation
	Before (%)	After (%)	Change	Contribution (%)
Jiangsu	68	72	0.06	50
Zhejiang	65	70	0.05	48
Guangdong	60	66	0.06	55
Shandong	63	67	0.04	40
Fujian	58	62	0.04	42
Hubei	55	60	0.03	35
Henan	50	53	0.02	30
Sichuan	52	56	0.03	38

IV. CONCLUSION

This study constructs a comprehensive framework based on entropy analysis, complex networks, and a spatial Durbin model to explore the relationship between economic fluctuations and the resilience of regional textile industry chains. The results show that enhancing industry chain resilience can significantly mitigate economic fluctuations and strengthen regional economic stability through spatial spillover effects, providing a quantitative basis for optimizing textile industry structure and policy formulation. The main limitation of this study is insufficient characterization of the time lag of shocks. Future research can combine high-frequency trading data and multi-agent simulations to further enhance the dynamic analysis capabilities of resilience evolution.

AUTHOR CONTRIBUTIONS

Li Yongjun designed, collected and analyzed the data, and drafted the manuscript. Li Yongjun conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Li Yongjun participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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